# Explainable Artificial Intelligence Models using Students' Academic Record Data, Tree Family Classifiers, and K-means Clustering to Predict Students' Performance

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***Abstract*—Academic systems work in a complex environment and face problems analysing students' performance using their current systems. Therefore, they use data mining to analyze an enormous set of data, get hidden and useful knowledge, and extract meaningful. Accordingly, the research aimed to analyze the performance of academic students by comparing the accuracies of each algorithm. Five classifiers of the tree family used for the experiments are J48, BF Tree, NB Tree, Random Forest, and REP Tree. The results indicated that J48 outperformed all the other tree family classifiers in terms of accuracy, precision and recall. Hence, it is a superior classification technique among the classifiers used for the educational datasets. Also, it has used labelled features to visualize an interpretable decision tree to indicate students' performance. Also, it has developed an interpretable model using the K-means clustering technique and the J48 tree.**

***Keywords—XAI, Student Performance, Tree Family, K-Means***

## I. Introduction

Artificial Intelligence (AI) plays a vital role in impacting our day-to-day lives and experience. Also, AI has been deployed in many research areas and rapidly grew to enhance the performance of such important systems, such as education [1] [2], healthcare [3], renewable energy [4], transportation and traffic [5], that directly.

For academic purposes, most academic institutes are currently connected with information systems to store data about students [5] [6]. All these sources are important to institute management to improve their decisions, resulting in the overall performance of learning outcomes. However, academic systems are working in a complex environment and faced problems analysing students' performance using their current systems. Accordingly, they need modern tools that help them survive and improve their overall performance. Students' information can be analyzed to discover which factors are more related to this case. The main challenges for universities are to evaluate their performance in-depth, assess their identity, and create a development strategy and future actions.

Therefore, they use AI tools to analyze an enormous set of data, get hidden and useful knowledge, and extract meaningful information from warehouses, data marts, and libraries. This information helps to make some decisions for improvement in the future. However, AI applications and models in the education field require transparency and explainability since an inaccurate prediction result may have severe consequences [7]. Moreover, academicians must understand AI applications' essential reasoning as a prerequisite for building trust in the predictions and adoption of AI applications [8]. Therefore, educational AI applications should be reliable and safe in accuracy metrics and transparent and explainable, primarily academic decision-makers [9]. So, AI researchers and practitioners have focused their attention on explaining the decisions made by AI applications such as Machine learning (ML) or Deep Learning (DL) require knowledge and understanding of the internal neural networks.

Explainability of AI applications (XAI) is a key part of trust among policymakers, education institutions, and its educational systems by providing insight and visibility [10]. Hence, AI's algorithms should provide academicians with understandable justifications for its output and understanding how AI application's inner workings [11]. For example, explainable prediction models of AI applications related to students' academic records can explain prediction results made for potential future students by revealing characteristics of current or historical students' records that led to the prediction output. Also, it identifies and explains why some students have achieved low results to help them in this regard. For example, a system may guide students where they could find better learning materials and may suggest some sites as well. Hence, it is improving the overall scenario of the educational institute. This study will use labeled features to visualise an interpretable decision tree to indicate students' academic performance. The paper structure is as follows: problem statement and research questions in Section 2. In section 3, related works with the main results. Research methods are detailed in Section 4 and experimental results in Section 5. The Artificial intelligence explainability in section 5. Conclusions and future work directions are drawn in Section 5.

## II. Problem Statement and Research Questions

Nowadays, education systems are working in a complex environment and face problems to determine students' performance using their current systems: high dropout rates, low quality of education, and academic results. Performance among students is an example of the common issues that influence the reputation of an educational institution. Also, due to the strong competition between academic institutes regards improving the level of learning outcomes, which is directly reflected in students' performance. Accordingly, they need modern tools that help them survive and improve their overall performance. So, they are using AI tools. It is a rising field that uses the data obtained from educational information systems to detect knowledge, find answers to questions and problems, and understand why they have achieved such results. Our study focuses on finding a solution that would help academic systems and management improve the decisions related to students' academic records, students' performance in particular. Also, understanding ML techniques' internal processes and results in educational systems is needed to make such critical systems more reliable and trustworthy to academicians and decision makers. XAI in educational systems impacts how end-users understand key decision results from these models. Therefore, it is necessary to balance the intricacy of the models (internal working process) and the accuracy of students’ performance as a compromise between the explainability and performance to find the ideal solution. This study will answer the following questions:

- What are the attributes that affect student achievement?
- What are the learning models that used to predict student performance?
- Can we Explain Artificial intelligence applications in education field?

## III. Literature Review

Al Mazidi & Abusham [12] applied data mining techniques to predict Oman's general diploma school students. Oman was the first country in the Middle East to collaborate technology with education. The decision-makers and stakeholders may be highly benefited with the huge volume of the educational data and take decisions by exploring the trends and patterns of the data. Dataset involved about 6000 students' records and 12 features over 3 years in this study. Tree Family algorithms showed the highest accuracy that reached 92.3%. They used SQL Server Analysis Services for data analysis and Transact-SQL for data modification. Unsupervised learning and association rule mining techniques were also explored.

In Nur Uylas Sati [13], Semi-supervised techniques are employed generally when there are some labeled samples and largely unlabeled fields. The machine learning tool used was WEKA. The accuracy of the classifiers was enhanced by pre-processing the data. Only the key attributes were taken into account for the classification task. Random Tree with local and global consistency (LLGC) were deployed. They collected the dataset from the UCI machine learning repository. The original dataset has 397 instances and 30 features but six attributes have selected using CfsSubsetEval function. The attributes were sex, parent’s cohabitation status, the reason to choose the particular school, number of past failures, romantic relations, second grade, and success.

Amjad Abu Saa et. al. [14] has used 56,000 students’ records with 34 attributes. The results indicted Random Forest has the best accuracy result with 75.52%. They revealed four different categories as the influential parameters in determining the performance. They were students’ previous performance, course and instructor information, general and demographic information of the students. Hussain (2017) surveyed current trends and techniques of data mining research. The author addressed the issues and challenges in this area along with different classifiers, open source tools and clustering algorithms applied in this area. He summarized data mining as evolving and vital research area used by computer scientists to biologists, educationists and statisticians [15].

A study was conducted by [16] to introduce an ensemble of regression and classification techniques to predict students' performance in an Open University. The early detection of low-performance students may improve the educational outcome by decreasing the dropout rates. The data was collected from Hellenic Open University. 3882 students’ records with 17 attributes were collected for 3 years. The attributes were distributed in three categories. They were a performance, contact session, and pre-university groups. A plethora of experiments was conducted to prove its efficiency. A prototype software support tool was also proposed and simulated the ensemble technique. The ensemble model was tested and compared with various state-of-the-art classification and regression methods. This method combined with the REPTree algorithms that attained the highest accuracy of 87.20%.

Tampakas, Livieris, Pintelas, Karacapilidis, & Pintelas, 2018 [17] presented a model which had two major characteristics. First of all, they accurately explored at-risk students. Secondly, students were classified according to their predicted graduation time. The dataset contained 282 instances of the bachelor's degree course was of 4 years’ duration. Therefore, they collected the data from the first 2 years of study and prediction was based on that. The total number of variables was 127 and was divided into two groups. The groups were demographic-based and performance-oriented attributes. The demographic attributes contained gender, age, home location, high school type, etc. and the performance-based attributes contained the type of course, number of times examined and the final grade in the course. The bachelor's degree program consisted of 41 courses subdivided into 25 core courses, 12 laboratory courses, and four clinical courses. The results of this model has achieved an accuracy of 78.73%.

A prediction model based on the students' academic performance using different data mining algorithms [18]. The influential attributes were also studied. She collected the data from a private institute Sree Saraswathy Thyagaraja College situated in Pollachi, India. As the college was located in a rural area, most parents were from agricultural families and backgrounds. The dataset was of 127 records. The parameters were gender, place, occupation, income, category, student higher secondary mark, and semester percentage. She had taken into account five different classification techniques.

They were Multi-Layer Perceptron (MLP), RepTree (REP), J48, Decision Tree (DT) and Naïve Bayes (NB). The predicted dependent attribute was placeable in a job. The algorithms were evaluated using ROC values. The average ROC values were 0.72, 0.70, 0.69, 0.68 and 0.58 for the NB, J48, DT, MLP and REP respectively. So, it was clear that NB outperformed the other classifiers.

This study developed by [19] to proposing a predictive model based on the grades achieved by the students in their earlier academic performance. They inferred a regression function using the demographic information of the students, examination records of the students and the final grade of each course. They applied Support Vector Machines, M5 Rules, Decision Trees, K-Nearest Neighbors, and Linear Regression Models. The total courses selected were eight. Based on first semester grades, the underperformed and at-risk students were identified. 592 students' records were used from an educational institute of Western Greece during two semesters and 18 attributes recognize each student in the dataset. The regression models were compared by applying Friedman Aligned Ranks tests. The performance of the Random Forest was the best with 8.66667 rank values. The other better-performing methods were LR and SMO with RBF Kernel.

In [20], they are collected and analyzed Common Entrance Examination data for admission to medical colleges of Assam of a particular year. This real dataset comprised 11 attributes and 666 records of the candidates who had qualified for the examination. They performed the association rule mining, classification techniques and clustering algorithms on the dataset. The data mining tools used for mining these educational records were R Studio, Weka and Orange.

## IV. Methodology

This section discusses the main processes that our research goes through to achieve the results and answering the research questions. The methodology processes were inspired from "Cross-industry standard process for data mining" and modified by adding explainability step (XAI: CRISP-DM) see Fig. 1.

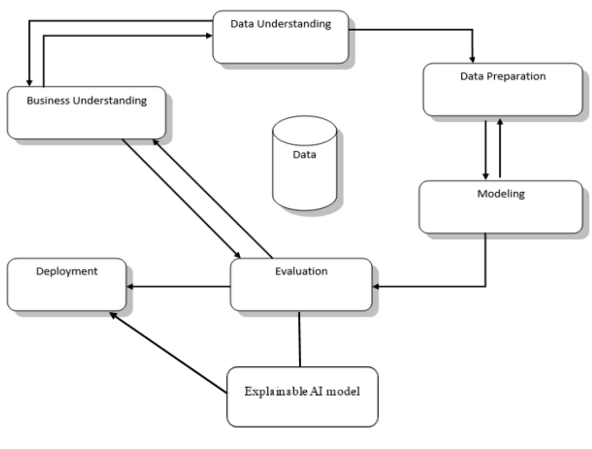


Fig. 1. XAI: CRISP-DM

### A. Phase 1: Understanding of Business

The main objective of this study is to propose a predictive model to predict student academic performance using data mining techniques. Also, compare between proposed classifiers based on evaluation metrics using historical datasets that related to students' records.

### B. Phase 2: Attributes of Data collection

To achieve the research goals, MIS dataset was used to build our models. The dataset contains different features from different countries that would help generalize our results. The tables below summarise the features numbers, instances, and reference of the MIS dataset (see Table I). The training set upholds a set of (27) features selected from the students' historical records of (1061) records along with class labels (student performance) of categories as Satisfactory (greater than or equal 50 and less than 68), Good (greater than or equal 68 and less than 75), Very Good (greater than or equal 76 and less than 68), and Excellent (greater than or equal 86 and less than 100). A big dataset was built from the MIS department at Amman University College/Al-Balqa Applied University in Al-salt (Jordan).

TABLE I. SUMMARIZES THE NUMBER OF FEATURES, INSTANCES AND REFERENCES FOR MIS DATASET

| Properties | MIS Dataset |
|---|---|
| Features | 27 |
| Records | 1062 |
| Male records | 450 |
| Female records | 612 |
| Classes | Four classes:<br>S: 41.50% (Satisfactory)<br>G: 27.00% (Good)<br>V. G: 25.80% (Very Good)<br>Ex: 5.70% (Excellent) |

### C. Phase 3: Data Pre-processing:

The preprocessing phase is essential in the knowledge discovery processes that involving data cleaning, selection of functions, data transformation, and data reduction. Accordingly, person correlation was adopted to select the best features that affected the students' performance. Fig. 2 shows the correlation values of MIS Dataset features from the highest to lowest values with prerequisite courses for some features concerning the class label. As shown, there are gradual correlation values among features in different feature type as follows: Compulsory Specialization Requirements (CSR) of 10 Computer Science (CS) courses gain a highest average correlation value of approximately 0.6, the Faculty Requirements (FR) of 7 MIS courses obtain a moderated average value of 0.53, the Compulsory University Requirements (CUR) of 5 courses have an average correlation value of 0.432, and the four demographic information exhibits a lowest average correlation value of 0.107.

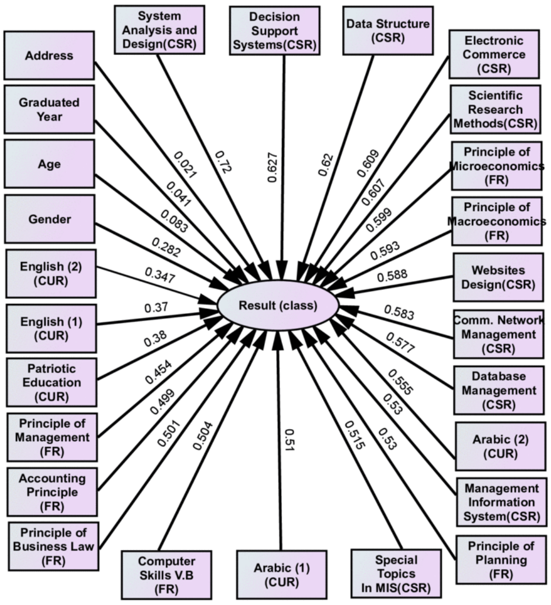


Fig. 2. Pearson's correlation values MIS dataset

As shown in Fig. 2, the results reveal strong correlations between all independent features and class feature (or students' performance) as values ranged between 0.720 for System Analysis and Design course as a feature while 0.021 was for the Address where students live.

### D. Phase 4: Applying Data Mining:

Based on reviewing literature, the most common techniques were Tree algorithms. Accordingly, the tree family methods were conducted as the main algorithms to build our model from the MIS dataset. The best selected parameters shown in Table II below.

TABLE II. PARAMETERS SITTING FOR J48 CLASSIFIER

| Option | Value | Description |
|---|---|---|
| Seed | 1 | To initialize the random number when reducing error pruning |
| Unpruned | False | Whether or not pruning |
| Confidence Factor | 0.25 | It uses for pruning. |
| Number of Folds | 3 | Size of the dataset for reducing error |
| Batch Size | 100 | Identify the number of instances in the batching process |
| Reduced Error Pruning | False | Reducing error of Pruning |
| Use Laplace | False | Whether counts at leaves are smoothed based on Laplace. |

### E. Phase 5: Testing and Evaluation

The dataset splits into 10 parts to build and evaluate our model using 10 cross-validation techniques to construct the prediction model. This technique takes nine parts as a training set and 1 to evaluate the constructed model. Then, iterate this phase 10 times, and the overall results are averaged for evaluation metrics. The main two evaluation metrics were used to evaluate each model and the results of each metric were calculated using the confusion matrix. Confusion matrix (or contingency table) is a method used in machine learning to visualise the performance of a machine learning method and compare the performance to other methods.

We focus on the following four measures: False Negative (FN), True Positive (TP), True Negative (TN) and False Positive (FP), each of which represents the performance of a particular classification. For example, TP used to classify the positive class for positive label. In FP, the rating is a positive class for the negative label, TN is negatively class for the negative label, and FN, the positive class for the negative label. There are also many existing criteria for determining the classification performance based on the confusion matrix data, such as recall, precision, F-measure, and Accuracy.

- Accuracy: It is the most widely used measure of the accuracy of the classification process, accuracy is normally obtained by the percentage of the correctly classified examples versus the total number of examples.

Accuracy =TP+TN/(TP+FP+TN+FN) ----------- (1)

- Precision: This measure helps to test the accuracy of the results obtained from the classifiers, which gives the exact percentage in the positive examples given to the total number:

Precision =TP/(TP+FP) ------------------ (2)

- Recall: This measure is used in the finalization test of the results from the classifier, which reflects the percentage of positive examples shown on the total number.

Recall = TP/(TP+FN) ------------------ (3)

## V. RESULTS:

Based on the main results in Table III, the best results showed that tree family outperforms others family. Therefore, the tree family methods are used for the experiments are J48, BF Tree, NB Tree, Random Tree and REP Tree. As shown in Table III, the accuracies of J48, BF Tree, NB Tree, Random Tree and REP Tree are 87.76%, 83.05 %, 86.54 %, 77.87 % and 85.22 %, respectively.

TABLE III. THE ACCURACY, PRECISION AND RECALL ON MIS DATASET FOR TREE FAMILY

| Algorithm | Accuracy | Precision | Recall |
|---|---|---|---|
| J48 | 87.76% | 0.879 | 0.878 |
| BF Tree | 83.05 % | 0.837 | 0.831 |
| NB Tree | 86.54 % | 0.871 | 0.865 |
| Random Tree | 77.87 % | 0.791 | 0.779 |
| REP Tree | 85.22 % | 0.856 | 0.852 |

While interpreting the results on three datasets, it is observed that J48 exhibits highest accuracy among the others. In other words, J48 outperformed all the other tree family classifiers in terms of accuracy, precision and recall. Hence, it is a superior classification technique among the classifiers used for the educational datasets.

## VI. AIX USING FEATURE SELECTION AND CLUSTERING TECHNIQUE:

The labelled features, Decision Tree, and K-means were used to explain the results of developed prediction model. Firstly, Pearson correlation was used to measure how the students' attributes are related to students' performance (or p-value < 0.01). Then, K-means also has used to group students' instances into three homogeneous clusters. Accordingly, it is notable that the feature of the System Analysis and Design course surprisingly influences the students' performance, which proves the fact that it highly affects their students' results (0.72). However, the lowest correlation to students' performance was the address of students. See Fig. 2 for more details. To explain the results, further analysis as shown in Fig.3 was created on System Analysis and Design course. The results have shown that the students with Excellent CGPAs are also having a high grade in System Analysis and Design course. Accordingly, we did future analysis on MIS course as its prerequisite course for System Analysis and Design course. As shown in Fig. 4 the results showed that a similar distribution for both courses with students' performance.

The results of the k-means algorithm are shown in Table IV which gives complete evidence how students records were distributed among the tree clusters. As shown in the table, students' scores are not the same in each cluster; this is indicated by the least and most grades. Also, the results showed that the cluster 3 concentrate on the students who have a high CGPA. Therefore, academic institutions must group their students and then focuses on preparing courses before they graduated.

This paper has used labelled features to visualize an interpretable decision tree to indicate students' performance. Also, it has developed an interpretable model using K-means clustering technique and J48 tree. K-means grouped students records into three clusters making each cluster more homogeneous with its characteristics, which revealed the most scores that are recorded by each cluster. Accordingly, it is notable that the factor of the System Analysis and Design course remarkably influences the students' performance, which proves the fact that it highly affects their final results. It can play a crucial role in achieving Excellent or Very Good results instead of obtaining Good or Satisfactory results. Therefore, academic institutions must focus on this course by preparing multimedia materials or giving them extra classes related to this course. On the other hand, the address attribute showed a low correlation to students' performance due to most of the students live in the same city, which is Amman due to the college located in Amman.

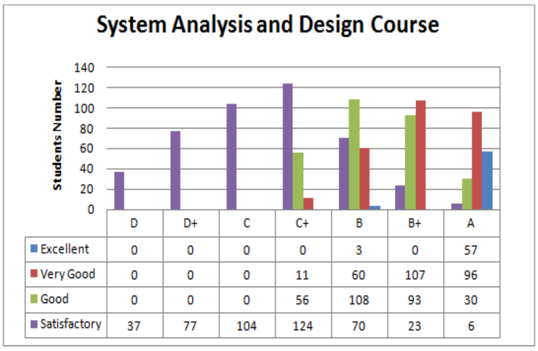


Fig. 3. GPA for SAD course

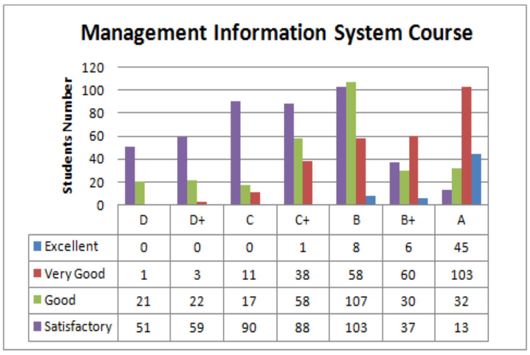


Fig. 4. GPA for the MIS course.

TABLE IV. THE SUMMARY OF K-MEANS

| Var | C1 | | C2 | | C3 | |
|---|---|---|---|---|---|---|
| | *Least* | *most* | *Least* | *most* | *Least* | *most* |
| CUR | C (16) | B (101) | A (16) | C+ (103) | D (7) | B+ (88) |
| FR | C (14) | C+ (108) | A (12) | C (103) | D (3) | A (94) |
| CSR | D+ (11) | B (114) | A (14) | C (99) | D+ (2) | A (139) |
| Gen. | M (149) | F (213) | F (186) | M (237) | M (64) | F (213) |
| Age | 21 | 41 | 21 | 35 | 21 | 44 |
| Gyear | 2006 | 2018 | 2006 | 2018 | 2006 | 2018 |
| City | Mfrak (3) | Amman (303) | Mfrak (1) | Amman (364) | Jrash (1) | Amman (241) |
| Class | V.G (4) | G (284) | G (1) | S (422) | G (2) | V.G (215) |

***V.G: Very Good; G: Good; S: Satisfactory***

## VII. CONCLUSION:

Educational Data Mining (EDM) is a sub-area of data mining where the emphasis is to improve the learning outcome of the educational institutions. The results indicated that the family decision tree performs better other family techniques. Also, it aims to build explainable prediction models of AI applications related to students' academic records to explain prediction results made for potential future students by revealing characteristics of current or historical students records that led to the prediction output. it has used labelled features to visualize an interpretable decision tree to indicate students' performance and developing an interpretable model using K-means clustering technique and J48 tree. Furthermore, the future work will include a larger dataset and other algorithms.

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